Early Diagnosis of Alzheimer's Disease: A Neuroimaging Study with Deep Learning Architectures

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Abstract

Alzheimer's Disease is an incurable, progressive neurological brain disorder. Early diagnosis of Alzheimer's Disease can help with proper treatment and prevent brain tissue damage. Several statistical and machine learning models have been exploited by researchers for Alzheimer's Disease diagnosis. Detection of Alzheimer's Disease is exacting due to the similarity in Alzheimer's Disease Magnetic Resonance Imaging (MRI) data and standard healthy MRI data of older people. Recently, advanced deep learning techniques have successfully demonstrated human-level performance in numerous fields including medical image analysis. We propose a deep convolutional neural network for Alzheimer's Disease diagnosis using brain MRI data analysis. We have conducted ample experiments to demonstrate that our proposed model outperforms comparative baselines on the Open Access Series of Imaging Studies (OASIS) dataset.

1. Introduction

Alzheimer's Disease (AD) is the most prevailing type of dementia. The prevalence of AD is estimated to be around 5% after 65 years old and is staggering 30% for more than 85 years old in developed countries. It is estimated that by 2050, around 0.64 Billion people would be diagnosed with AD [2]. Alzheimer's Disease destroys brain cells causing people to lose their memory, mental functions and ability to continue daily activities. Initially, Alzheimer's Disease affects the part of the brain that controls language and memory. As a result, AD patients suffer from memory loss, confusion, and difficulty in speaking, reading or writing. Ultimately, AD destroys the part of the brain controlling breathing and heart functionality which lead to death. There are three major stages in Alzheimer's Disease - very mild, mild and moderate. Detection of Alzheimer's Disease (AD) is

still not accurate until a patient reaches moderate AD. We propose a deep learning model to identify different stages of Alzheimers Disease. Our primary contributions are threefold:

- We propose a deep convolutional neural network that can identify Alzheimer's Disease and classify the current disease stage.

- Our proposed network learns from a small dataset and still demonstrates superior performance for AD diagnosis.

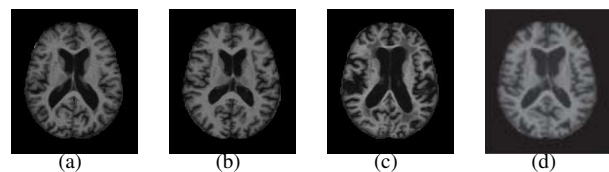- We present an efficient approach to training a deep learning model with an imbalanced dataset.

Figure 1. Example of different brain MRI images presenting different AD stage. (a) Nondemented; (b) very mild dementia; (c) mild dementia; (d) moderate dementia.

2. Related work

Alzheimer's disease has a certain progressive pattern of brain tissue damage. It shrinks the hippocampus and cerebral cortex of the brain and enlarges the ventricles [11]. Figure 1 shows some brain MRI images presenting different AD stages. Some remarkable research works have been done for automated Alzheimer's Disease diagnosis. For example, Aversen et al. [1] used dimensionality reduction methods, Brosch et al. [3] developed a deep belief network model, Gupta et al. [4] developed a sparse autoen-

coder model and Payan et al. [10] combined sparse autoencoders and 3D CNN model for AD detection and classification. Earlier we developed a very deep convolutional neural network [6] using transfer learning for AD diagnosis. Here, we improved the previous model and developed a deep convolutional neural network and demonstrated superior performance on the OASIS dataset [9].

3. Proposed methodology

Our proposed model is a deep convolutional neural network as shown in Figure 2. The model has several layers performing four basic operations - convolution, batch normalization, rectified linear unit, and pooling. The layers in the model follow a particular connection pattern known as dense connectivity [3], where each layer is connected to every other layer. For final classification, there is a softmax layer with four different output classes: nondemented, very mild, mild and moderate AD. For each MRI data, we created patches from three physical planes of imaging: Axial or horizontal plane, Coronal or frontal plane, and Sagittal or median plane. These patches are fed to the proposed network as input. This data augmentation technique increases the number of samples in the training data set. The size of each patch is 112*112. To handle the imbalance in the dataset, we have used cost sensitive training [8]. A cost matrix ξ was used to modify the output of the last layer of the network. Since the less frequent classes (very mild dementia, mild dementia, moderate dementia) are underrepresented in the training dataset, the output of the network were modified using the cost matrix ξ to give more importance to these classes. If o is the output of the individual model, p is the desired class and L is the loss function, then y denotes the modified output:

$$y^i = L(\xi_p, o^i), : y_p^i \geq y_j^i \forall j \neq p \qquad (1)$$

The loss function is modified as:

$$L = -\sum_n t_n log(y_n) \qquad (2)$$

where y_n incorporates the class-dependent cost ξ and is related to the output o_n via the softmax function [8]:

$$y_n = \frac{\xi_{p,n} exp(o_n)}{\sum_k \xi_{p,k} exp(o_k)} \qquad (3)$$

The weight of a particular class is dependent on the number of samples of that class. If class r has q times more samples than those of s, the target is to make one sample of class s to be as important as q samples of class r. So, the class weight of s would be q times more than the class weight of r.

4. Experiments and results

To validate the effectiveness of the proposed Alzheimer's Disease diagnosis model, we have developed two baseline deep CNN, Inception-v4 [12] and ResNet [5] and modified their architecture to classify 3D brain MRI data. We have considered four metrics for quantitative evaluation and comparison, including accuracy, precision, recall, and f1–score. The OASIS dataset [9] has 416 data samples. We have divided the dataset into a training and test dataset in 4:1 proportion. A validation dataset was prepared using 10% data from the training dataset.

Table 1. Performance of the proposed model on OASIS dataset.

Class	precision	recall	f1–score	support
non-demented	0.99	0.99	0.99	73
very mild	0.75	0.50	0.60	6
mild	0.62	0.71	0.67	7
moderate	0.33	0.50	0.40	2

We applied the SGD training with a mini-batch size of 64, a learning rate of 0.01, a weight decay of 0.06 and a momentum factor of 0.9 with Nesterov optimization. Table 1 shows the performance of the proposed model on the OASIS dataset [9]. Here, we can see the precision of the proposed model is 99% for non-demented stage, 75% for very mild stage, 62% for mild stage, and 33% for moderate stage. So, though the model has acceptable performance for nondemented patient classification, it still has a lot of scopes to improve for demented patient diagnosis. Training the proposed model with dataset having more samples for demented patients could help to improve this limitation. The classification performance of the two baseline deep CNN models are presented in Table 2 and Table 3, respectively. For object detection and classification, Inception-v4 [12] and ResNet [5] have already demonstrated outstanding performance. But due to the lack of enough training dataset, both models suffered overfitting and showed poor performance for AD diagnosis. Compared to these baseline models, the proposed model achieves encouraging performance for classifying different stages of Alzheimer's Disease.

5. Conclusion

We have demonstrated an efficient approach to Alzheimer's Disease diagnosis using brain MRI data analysis. While the majority of the existing research works focuses on binary classification, our model provides significant improvement for multi-class classification. Our proposed network can be very beneficial for early-stage Alzheimer's Disease diagnosis. Though the proposed model has been tested only on Alzheimer's Disease dataset, we believe it can be used successfully for other classification problems of medical domain. Moreover, the proposed
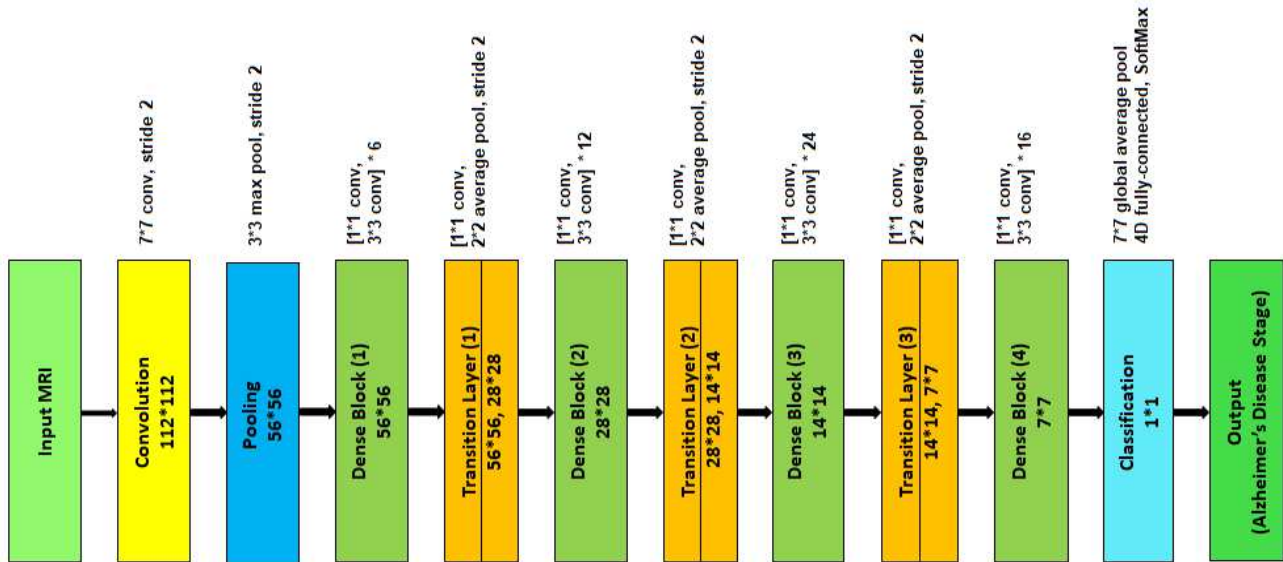
Figure 2. Block diagram of proposed Alzheimer's Disease diagnosis framework.

approach has strong potential to be used for applying CNN into other areas with a limited dataset. In future, we plan to evaluate the proposed model for different Alzheimer's Disease dataset such as ADNI [7] and other neurological disorder diagnosis.

Table 2. Performance of Inception-v4 [12] model on OASIS dataset.

Class	precision	recall	f1–score	support
non-demented	0.81	0.91	0.86	73
very mild	0.0	0.0	0.0	6
mild	0.30	0.30	0.30	7
moderate	0.0	0.0	0.0	2

Table 3. Performance of ResNet [5] model on OASIS dataset.

Class	precision	recall	f1–score	support
non-demented	0.82	1.00	0.90	73
very mild	0.0	0.0	0.0	6
mild	0.0	0.0	0.0	7
moderate	0.0	0.0	0.0	2

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